Getting Beneath the Veil of Intergenerational Mobility: Evidence from Three Cities

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Abstract

Intergenerational mobility is one of the most important social issues of our time. We collected data from in-person surveys of almost 1,000 individuals who were reared in poverty in Memphis, Tulsa, and New Orleans, and asked about their childhood health, parental income, home environment as a child, childhood experiences, lifetime traumas, neighborhood safety, a host of psychological skills, beliefs, and current income. Typical descriptive approaches implicitly assume one can alter individual characteristics in any way the data deem predictive – e.g. sending youth to college who have been the victims of abuse – even if one rarely observes that combination of characteristics in the data. We relax this assumption and use the distribution of covariates to understand how variables relate to one another and estimate the expected costs of altering any combination of individual characteristics, using a measure of statistical distance. We find that educational attainment is the most important determinant of mobility. Yet, many other variables – traditionally ignored by economists – are almost equally important predictors: resilience, Big 5 personality skills, grit, self-esteem, the number of adults trusted, trouble with the police when young, and other adverse childhood experiences. Fathers present in own neighborhood did not matter. This suggest that income-increasing interventions for the poor need to be broader than simply human capital or place-based policies.

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1 Introduction

Concerns about poverty and intergenerational mobility are as old as civilization itself.[1] Thousands of years later, poverty and intergenerational mobility are, still, among the most important economic and social issues of our time. In an average OECD country it would take four to five generations for children in the bottom earnings decile to attain the level of mean earnings, but there is significant heterogeneity across countries and between ethnic and racial groups within countries. OECD's annual report on social mobility estimates it will take two generations for children in the bottom decile in Nordic countries to reach the mean; four to six generations across Europe, and five generations in America (OECD, 2018).

Within the US, differences across racial groups are stunning. For some, America is the land of unparalleled opportunity. For others, it is the land of the ineludible poverty trap. In parallel work, Chetty, et al (2018) employ a large new dataset – linking census data covering the U.S population to federal income tax returns from 1989 to 2015, a total of 20 million observations – to estimate intergenerational mobility in America, by race and for granular geographies, providing more precise estimates than Solon (1992).[2] They find that black Americans have lower rates of upward mobility and higher rates of downward mobility compared to white Americans and on par with Native Americans. Blacks in the top income percentile have male children who are as likely to be incarcerated as whites in the 20th percentile.

Gaining a better understanding of intergenerational mobility is of great importance. If, by accident of birth, certain individuals are not able to achieve their full potential then there are important imperfections in the market for talent and making that market more meritocratic may have large social value.

A wide variety of possible correlates of intergenerational mobility have been put forth. These include education and school quality (Aldaz-Caroll and Moran, 2001; McKernan and Ratcliffe, 2005; Haskins, 2008; Baum, Ma and Payea, 2013), neighborhood quality (Keels et al., 2005; Sanbonmatsu et al., 2012; Chetty et al., 2014; Chetty et al., 2016; Chetty and Hendren, 2018), early childhood and adverse childhood experiences (Duncan and Rogers, 1988; Aldaz-Carroll and Moran, 2001; Metzler et al., 2017), family structure and parenting (Duncan and Rodgers, 1988; Aldaz-Carroll and Moran, 2001), and church going and other forms of social capital (Freeman, 1986; Sharkey and Torrats-Espinosa, 2015; Western and Pettit, 2010).

In this paper, we attempt to shed new light on the correlates of mobility in America using new data from in-person interviews of approximately one thousand families – all of which self-report growing up poor – in Memphis, Tennessee, New Orleans, Lousianna, and Tulsa, Oklahoma.

Interviews were conducted in a respondent's home or a public place, whichever was preferred, and lasted

[1] In the oldest written text, "Gilgamesch", there are mentions of famine and descriptions of poverty are in Confucius writings, the Iliad, and the Odyssey. Inequality and mobility were discussed in Ancient Egypt during the rein of King Akhenaten – 80% of the wealth of the belonged to 20% of the population.

[2] Solon (1992) used the PSID dataset and corrected for measurement error to show that the correlation between fathers' earnings and sons' earnings is approximately 0.4. This proved that US was not as highly mobile a society as was previously believed – previous estimates of the correlation were of the order of 0.2.

almost two hours.[3] At the end of the interview, the respondent received a pre-paid $150 Visa gift card. Our final sample consists of 928 respondents for the full interview.

The extensive length of our face-to-face interviews allowed us to collect a wide-ranging set of data: basic demographics, mental health, physical health, parental behavior, home environment, childhood experiences, risky attitudes as a teenager, lifetime traumas, neighborhood safety, and psychological skills such as the Big 5 personality traits, grit, locus of control and resilience. Our main outcome variable is log household income in 2016, though we also present results for individual income, adult mental and physical health, and drug and alcohol use.

The results we obtain from these new data are informative, surprising, and inspire the development of new methods. Using typical descriptive approaches, such as those implemented in Garces, Thomas and Currie (2002), the correlates of intergenerational mobility are education, resilience, mental health before age 16, trouble with police before age 18 and grit. Variables such as childhood abuse, parenting, teenage risky behaviors, trust in adults, or other psychological skills are seemingly not important. Moreover using standard descriptive methods to identify which variables are important, when the number of covariates is high, tend to generate results that are not robust to minimal changes in sample size or variable definitions (Mullainathan and Spiess, 2017).

This inspired us to think about the approaches used in the literature. Least Squares estimates or popular supervised learning algorithms both assume one can alter individual characteristics in any way the data suggest is optimal – even if one rarely, if ever, observes individuals in the data with those combinations of characteristics. Consider the following thought experiment. Imagine that graduating from college has large causal effects on future income for everyone, but it's extremely rare that individuals who have endured childhood abuse graduate from college. Just estimating typical descriptive methods – trying to predict income conditional on observables – may tell us to simply get everyone to graduate from college and this will improve their income. But it won't tell us if it's possible!

We relax this assumption and use the distribution of covariates to understand how our variables relate to one another and estimate the costs of altering any combination of individual characteristics. In the thought experiment above, this implies that if we observe the lack of childhood abuse and college graduation typically covary, we infer that it is difficult to ensure that victims of childhood abuse graduate from college. And, thus, any income-increasing intervention may want to target both. Our approach boils down to a simple maximization problem with two key parameters: the distribution of individual characteristics and the distribution of the outcome variable, conditional upon those characteristics. We provide both parametric

[3] To screen potential survey respondents, individuals were first contacted by phone. A respondent was deemed eligible if: (1) they resided in a zipcode in our desired geographies; (2) were at least 18 years of age; (3) self-identified as having "grown up poor" (e.g. answered "Do you consider yourself to have grown up poor?" in the affirmative). This initial conversation lasted, on average, six minutes, and allowed us to collect information on basic demographics, education, and preferred contact information for all eligible respondents. In total, 457,317 phone calls were made and 6,459 were completed.

and non-parametric estimates of the correlates of income mobility using our newly collected data and new methods. We believe this method can be used anytime one wants to use observational data to better optimize social experiments designed to increase some desired outcome (e.g. test scores, labor market participation, income in developing countries).

When we use the distribution of characteristics to inform how variables move together, the correlates of intergenerational mobility are quite different. Education is still the most important factor in intergenerational mobility. Of the eight other correlates that are significant, however, five of them are psychological skills: resilience, the Big 5, self-esteem, self-control, and grit. The remaining three are whether the respondent was in trouble with the police in their youth, the number of adverse childhood experiences – such as abuse – and the number of adult relationships they trusted during their childhood. The fact that education is the most persistent correlate of mobility is consistent with more than a half century of scholarship in economics. Beginning with Blau and Duncan (1967) and formalized in Becker and Tomes (1979), the model of mobility has been the quantity of skills and their prevailing market price. Our results, along with the burgeoning literature on the importance of non-cognitive skills, suggest a much larger set of skills and experiences are important to produce income. Admittedly, the importance of psychological skills in the production of earnings is not a new idea – Heckman et al. (2006) state that "...for many labor market outcomes, a change in noncognitive skills...has an effect on behavior comparable to or greater than a corresponding change in cognitive skills" – but its relative importance to human capital and family environment is striking.

Variables that capture place-based heterogeneity such as the neighborhood specific probability of the bottom 25 in top 20 percentile are not significant in our main specifications. However, consistent with Chetty et al. (2018) we find that high mobility zipcodes are significantly more helpful to whites.

We explore the robustness of our results across various measures of income, alternative specifications, and alternative measures of adult well-being. Our results are virtually unchanged when using adjusted household income or individual income as outcomes variables. Alternative specifications, such as allowing for heterogeneity in the distribution of individual characteristics or not adjusting for poverty levels as a child, also yield similar results. Interesting differences do emerge when we use mental illness, or drug and alcohol use as alternative measures of adult well-being. The most important correlates of mental illness include various psychological skills, risky behaviors as a teenager, mental and physical illness as a teenager, education, adverse childhood experiences, family environment, interactions with police, number of adult relationships trusted, neighborhood mobility and an index of neighborhood safety. The latter is consistent with data gleaned from the Moving to Opportunity experiment (Sanbonmatsu et al., 2012).

Similarly, the most important correlates of adult drug and alcohol use are self-control, risky attitudes as a teenager, whether an individual was in trouble with police as a youth, mental health, relationship with parents, neighborhood safety, family environment, and adverse childhood experiences. While education was the most persistent predictor of income, it is a significantly less important predictor of adult mental illness or drug and alcohol use as an adult.

Our analysis has three important caveats. First, the locations are not representative. We chose them because they are representative of a signficant share of black poverty in America. Appendix Table 1 compares our survey sample to a comparative sample of National Longitudinal Survey of Youth 1979 (hereafter NLSY) respondents who were between the ages of 14 and 22 *and* below the poverty line in 1979. Strikingly, our sample – taken from these three cities – is statistically similar to the unadjusted nationally representative data on most demographics. The only variables that are statistically different are age and percent Hispanic.

Second, our survey design requires adults to remember their childhood details with a degree of specificity and objectivity that may be implausible.[4] Adding to this complication, our variables designed to assess psychological capital and beliefs – grit, growth mindset, resilience, and so on – are contemporaneous. It is plausible that increasing ones income from childhood poverty causes one to remember childhood experiences in a different light, tell oneself a different narrative or feel more resilient. We had to choose between our current design, which has important shortcomings, and starting a longitudinal dataset similar to the NLSY and waiting at least two decades for the results.[5]

One way to try and understand how this may affect our results is to analyze any individual characteristics in our data that may have been sampled multiple times in a known longitudinal dataset. NLSY, for instance, assessed the locus of control of its respondents in 1979 when individuals were 14 to 22 and again in 2014 when they were older adults. The correlation between locus of control and income in our data is equivalent to correlating 2014 income with 2014 measures of locus of control in the NLSY; both are positive and significant. Importantly, this correlation in the NLSY exists and is of similar magnitude whether one correlates the 2014 measure of locus of control with 2014 income or the 1979 measure of locus of control with 2014 income. Put differently, it seems that there is a strong correlation between measures of locus of control in youth and adult income and that correlation is almost identical if one uses a measure of locus of control assessed in adulthood.

Third, which is less caveat than clarification, our results are correlates of income and other measures of adult well-being which suggest what types of interventions will be most successful – not causal estimates.[6] Without a well-powered field experiment or valid instrument, thorny issues of self-selection, omitted variable bias, and the like may influence our results. Yet, a separate set of issues exist with field experiments. They

[4]There is some evidence that individuals are more likely to discuss sensitive topics such as abuse with strangers after the fact and not necessarily contemporaneously (Alaggia, 2010).

[5]Another possibility was to ask parents or friends about the respondent when they were young. This might provide a measure of psychological capital when the respondent was young or a different perspective on sensitive issues such as abuse. This method is similarly problematic and, for a fixed budget, reduces our sample size significantly. We chose a larger sample.

[6]Yet, evidence from experiments or natural experiments, suggests that 7 of our identified correlates of income mobility seem to have a causal effect as well . For instance, Angrist and Krueger (1991) demonstrate that compulsory schooling laws increase years of schooling and hence, higher wages. Heckman et al. (2013) show that participants of the HighScope Perry Preschool Program have higher measures of the Big 5 personality traits and increased monthly income at age 27.

produce clear causal estimates but, without understanding the underlying production function of mobility, may be unlikely to yield positive results. We view our approach and field expeeriments as strong complements. This paper is an important first step in a larger research agenda whose aim it is to take these correlates and conduct a large scale randomized control trial with a subset of them, aiming to increase intergenerational mobility and overall life outcomes of those who, by circumstance of birth, are more susceptible to continue to be low income in future generations.[7]

With the above caveats and clarifications in mind, our paper makes three contributions. First, we collect new detailed data on individuals who were born into poverty. This data is more comprehensive than previous datasets, including information on sensitive issues such as abuse, relationships with parents and other adults, interactions with police, mental and physical health, learning disabilities, and so on. Second, since Fisher (1925), randomized control trials (RCTs) have grown tremendously in use and importance.[8] The methods developed provide a way to use rich observational data to potentially make those experiments more effective, which could save billions of dollars and alter millions of lives. Third, the results from our new data and new approach, offer an innovative way forward for increasing intergenerational mobility in America.

The paper is organized as follows. The next section details our sample frame and the data collected for our analysis. Section 3 describes our methods and section 4 reports empirical results from combining the new methods and data. Section 5 discusses our findings in the context of the previous literature and concludes. There are 6 appendices. Appendix I and II are guides to the implementation of our pilot and main survey. Appendix III has data descriptions of all datasets used in the paper and their variables. Appendix IV contains all proofs. Appendix V and VI show the phone and paper survey questionnaires.

2 A New Survey of Intergenerational Mobility in America

A. Design

In choosing which cities to conduct our survey, we were interested in selecting areas with high levels of poverty, ethnic diversity, and geographic variety. We settled on the general areas of Memphis, TN, Tulsa, OK, and New Orleans, LA. To more precisely define the areas, we started with the Metropolitan Statistical Areas that contained these cities and then selected four counties within them: Shelby County, Tulsa County, and Jefferson and Orleans Parishes. Shelby County has a population of 936,961 with 54.1% black, 6.4% Hispanic, and 35.9% non-Hispanic white. Twenty-one percent of the population currently lives in poverty.

[7]A similar approach was used in Dobbie and Fryer (2013) and Fryer (2015) in an effort to increase student achievement.

[8]The intellectual development of RCTs is varied. Many are theory driven – testing important social scientific theories in the field (e.g. The impact of teacher specialization on student achievement, Fryer 2018). Others seem more resource driven – the federal government spends $565 billion per year on medicaid and we don't know how effective these investments are (Finkelstein et al., 2012). And, many are impact driven – understanding how best to increase student achievement, employment rates, income in third world countries, or reduce crime. Our method applies to the last category.

Tulsa County has a population of 646,246 with 10.8% black, 12.7% Hispanic, and 60.2% non-Hispanic white. Sixteen percent of the population currently lives in poverty. Since the counties in the New Orleans MSA had smaller populations, we selected two: Jefferson and Orleans Parishes. Jefferson Parish has a population of 439,036 with 27.6% black, 14.9% Hispanic, and 52.5% non-Hispanic white. Sixteen percent of the population lives in poverty. Orleans Parish has a population of 393,292 with 60.1% black, 5.7% Hispanic, and 30.7% non-Hispanic white. Twenty-four percent live in poverty.

B. Sample Selection Method

After determining our sample areas, the next step was to decide how to select our sample within those areas. Previous surveys have often relied on address-based sampling (ABS) to help ensure a representative sample. For example, in the National Longitudinal Survey of Youth 1979, interviewers went to a random sampling of housing units and performed a short screener in person. Although this method is often considered the gold standard for in-person interviews, it is also very expensive. An alternative method of screening is by phone. In order to determine if the samples obtained by phone-based screens and ABS were comparable, we ran a pilot study in Los Angeles County, California, consisting of 643 residents. After comparing the two samples and finding no significant differences in the demographics of the populations surveyed, we selected the phone screening method as it is much more cost-effective and allowed us to interview more individuals for our final sample. (See Online Appendix II for a full methods report on our survey design). Abt Associates was responsible for the implementation of both the pilot and full interview.

C. Phone screens

In order to be eligible for the full interview, individuals had to reside in a zip code that was in one of our sampling counties, be at least 18 years old, and self-identify as having grown up poor. Sixty-five percent of the screening frame came from a cell phone screened sample, and thirty-five percent came from a landline screened sample. During the phone screen, we collected information on basic demographics including gender, race, education and contact information for those individuals who were eligible. (See Online Appendix V for the full text of phone screen). The phone screens lasted an average of 6.3 minutes. In total 6,459 phone screens were completed in our three sampling areas: 1,227 were eligible and agreed to participate in the full interview, 1,390 were eligible but refused further participation and 3,842 were ineligible. (See Table C, Online Appendix II for full distribution of respondents by location).

D. Interviews

For subjects who were eligible and agreed to participate, in-person interviews were scheduled. These interviews lasted an average of 104 minutes; approximately 350 questions were asked. The majority of interviews were conducted in individuals' homes, although interviewers were also willing to meet with respondents in public places like coffee shops or the library if the respondent preferred. At the end of the interview, the respondent received a prepaid $150 Visa gift card. During the interviews, we asked questions on a wide variety of topics. We incorporated topics that have been considered potential causes of poverty in the literature and focused on questions and psychological scales that have been developed and validated in previous studies. Below, we describe the general categories of topics we were interested in along with some of the major subsections. [9]

E. Income and Adult Well-Being

The main outcome variables used in our analysis are (log) individual income and household income in 2016 in dollars, a series of detailed questions designed to assess mental health, and a set of questions to assess drug and alcohol abuse. Of 928 respondents, 764 were willing and able to answer the income question in an open-ended format. If a respondent said that she did not know or want to answer, we asked her if she would be willing to tell us what range it fell within ($0-$10,000; $10,000-$20,000; $20,000-$30,000; $30,000-$40,000; $40,000-$50,000; $50,000-$75,000; $75,000-$100,000; $100,000-$150,000 or more than $150,000) and then assigned her the midpoint of that range.

Beyond income, we analyze two additional measures of adult well-being: mental illness and drug and alcohol abuse. To assess these measures, we used the industry standard instruments for screening in clinical settings. This includes CAGE-AID: a questionnaire developed to screen for drug use (Basu et al., 2016); GAD 7: a 7-item self-administered questionnaire developed to measure and assess generalized anxiety disorder (Spitzer et al, 2006); and PHQ-9, a 9-question instrument used for screening, diagnosing, monitoring, and measuring the severity of depression (Spitzer et al 1999). These instruments have been used widely in research and clinical practice and generally have been shown to have superior validity when compared to alternative screening questionnaires as well as reliability with independent diagnoses conducted by mental health professionals (Kroenke, Spitzer and Williams, 2001; Lowe et al, 2004; Brown et al, 1998; Brown and Rounds, 1995; Spitzer et al, 2006). See Online Appendix III for details.

F. Other Variables

Basic Demographics

[9] The full interview text is available in the Online Appendix VI.

We collected a number of demographic variables in both the phone screen and full interview. This includes gender, race (coded as white, black, Hispanic or other), age, current household members, and highest level of education completed. Our education variable asked individuals to classify themselves as not completing high school, having a high school degree/GED/some college, having a two year Associate's degree, or having at least a Bachelor's degree.

Parental Income

Although we do not contain actual estimates of parental income, we collected variables that proxy for parents' economic conditions. These include participants' responses to questions about whether their families were well off, average or poor financially; whether they ever moved due to financial difficulties or ever received help due to financial difficulties; if there was a time when the father was unemployed for several months; if the mother ever received welfare; and the frequency with which their families (a) found it difficult to afford child care, (b) fell behind rent or mortgage payments, (c) fell behind gas, electric or phone bill payments, (d) were unable to pay for transportation to get to work or school, (e) were unable to afford medical care, (f) had trouble paying a credit card balance, and (g) had too little money to buy enough food. To ensure that we are targeting people who grew up poor only, we drop participants who say that they had grown up "well off". This reduces the sample size by 28 respondents.

Early Home Environment

These variables were meant to capture the environment that an individual was raised in through questions about childhood household composition, neighborhood safety, and financial difficulties in their childhood. Questions were mainly drawn from surveys administered as part of the Moving to Opportunity experiment and the Health and Retirement Survey. We were particularly interested in looking at the roles and practices of parents or parental figures and other important relationships in childhood. We relied on the Short Version of the Family Environment Survey, a 27-item inventory designed to measure social-environmental characteristics of the family that was developed by Rudolf Moos and Bernice Moos in 1994. This scale features items such as "Family members had strict ideas about what is right or wrong" and "There were very few rules to follow in our family" and asked respondents to state whether these statements were true or false of the family they lived with between the ages of 5 and 12. Additionally, we adapted questions from the Parent Practices Survey, a 34-item self-reported instrument designed by Dr. Joseph Strayhorn to understand parents' patterns of interaction with their preschool children. In a sample of 200 low-income parents, the scale had good internal consistency and 6-month stability (Strayhorn and Weidman, 1988) and was associated with measures of parents' psychological and social health. Since the original survey was targeted towards parents, we reworded questions to ask respondents their perceptions of their parents' attitudes. For example, "How often does this child do something that gives you pleasure and enjoyment" was rewritten as “How often would your parent say that you did something that gave him/her pleasure and enjoyment?”

Childhood Traumas and Risky Behaviors

Our main instrument for assessing childhood trauma is the questionnaire from the Adverse Childhood Experience (ACE) study, a 10-item self-reported measure developed to quantify cumulative childhood stress (Felitti et al., 1998). The study, and further follow ups, repeatedly found a relationship between negative later life health outcomes (e.g. alcoholism) and increasing numbers of stressors (e.g. an ACE). ACEs include items such as whether an individual experienced childhood physical or sexual abuse, negligence, witnessed the physical abuse of another household member or whether another household member was mentally ill or addicted to drugs. We investigate whether this relationship continues to be robust in a population of mainly low income individuals and if applied to outcomes outside of the health domain. Additionally, we used a list of lifetime traumas that an individual may have experienced before the age of 18 (such as being in trouble with the police, repeating a year of school or being abandoned by his parents) along with questions on childhood health that were taken from the Psychosocial and Lifestyle Questionnaire of the Health and Retirement Survey. Questions about an individual’s experience with drugs and alcohol during childhood were drawn from the 2013 National Youth Risk Behavior Survey. Finally, questions about risky attitudes and behaviors during adolescence were taken from the Moving To Opportunity Child Questionnaire.

Psychological Skills

We chose a broad spectrum of psychological scales, some of which have been tested in large surveys previously (e.g. Rotter’s locus of control scale), as well as some that have been developed more recently (e.g. Grit Scale, Dweck Mindset Instrument). Where available, we used abridged scales to limit the length of the survey. Below, we describe a selection of these scales.

The Brief Resilience Scale is a 6-item scale developed by Smith et al. in 2008 to assess the ability to recover from stress. It has been examined in samples of students as well as chronic pain and cardiac patients and found to be reliable and negatively related to mental and physical health symptoms including anxiety and depression. The scale includes items such as “I tend to bounce back quickly after hard times” and asks respondents to state whether they strongly disagree, disagree, neither agree nor disagree, agree, or strongly agree. A meta-analysis of various resilience scales used in the field found that the Brief Resilience Scale was among one of the highest rated scales in terms of construct validity and internal consistency (Windle et al., 2011).

The Brief Self-Control Scale (BSCS) was developed by Tangney, Baumeister and Boone in 2004 and is used to measure the five domains of self-control: self-discipline, resistance to impulsivity, healthy habits, work ethic and reliability. The scale was found to have good internal consistency and retest reliability. Higher scores on the self-control scale were correlated with lower rates of alcohol abuse, higher grade point averages and better interpersonal skills. The BSCS has been used in over 100 published studies on adolescents and adults to predict numerous behavioral outcomes including high school achievement, job-searching behavior, binge eating and work performance (Lindner et al., 2015; Duckworth and Seligman, 2005; Baay et al., 2015; De Ridder et al., 2012)

Rotter's locus of control scale is a 23 item scale developed by Julian Rotter in 1966 to assess the extent to which an individual feels he can control his circumstances and outcomes. We used an abridged version that relied on four items to mirror the version used in NLSY79. Each item contains two statements (e.g. A. In my case getting what I want has little or nothing to do with luck and B. Many times we might just as well decide what to do by flipping a coin.) and asks respondents to select which statement is closer to their opinion. The four-item version used in NLSY was found to correlate with schooling decisions, employment and wages (Heckman et al., 2006; Darity et al., 1997).

The Dweck Mindset Scale was developed by psychologist Carol Dweck and is used to differentiate between a fixed mindset, in which individuals believe basic qualities like intelligence are fixed traits, and a growth mindset, in which individual believe that their abilities can be developed. A study of high schoolers in Chile found that having a growth mindset strong predicted academic achievement, particularly among low-income students (Claro et al., 2016). Similarly, a longitudinal study of middle school students found that those with a growth mindset outperformed students with a fixed mindset in mathematics two years later (Blackwell et al., 2007). We used an abridged 3-item version that focuses on fixed views of intelligence such as "Your intelligence is something about you that you can't change very much" (Dweck, 1999).

The Rosenberg Self Esteem Index is a 10-item scale developed by Dr. Morris Rosenberg in 1965 to measure both positive and negative feelings a respondent may have about himself. It has been widely used across fields and in large surveys including in the NLSY79. In the NLSY79, higher measures of self-esteem were correlated with future economic success (Heckman et al., 2006). Respondents are asked to indicate their level of agreement with statements such as "On the whole, I am satisfied with myself" and "I feel I do not have much to be proud of."

The original 12-item Grit Scale was developed by Duckworth et al. in 2007 and is meant to measure the ability to sustain effort towards long-term goals. We used the 8-item Short Grit Scale which has been found to correlate with retention in cadets attending West Point, higher educational attainment and fewer job changes among adults (Duckworth et al., 2007; Duckworth and Quinn, 2009). The 8-item scale contains statements like "New ideas and projects sometimes distract me from previous ones" and "I often set a goal but later choose to pursue a different one" and asks respondents to indicate their agreement with the statement on a five-level Likert scale.

To assess personality traits, we first started with the the International Personality Item Pool, a site with over 3,000 items and 250 scales that are used to measure personality traits (Goldberg, 2006). We selected the 50-item sample questionnaire based on Goldberg's markers for the Big-Five domains of personality: extroversion, agreeableness, conscientiousness, emotional stability, and intellect (Goldberg, 1992). The 50-item Big-Five scale (IPIP) has good internal consistency and related strongly to two other leading personality questionnaires – NEO Five Factor Inventory and Eysenck Personality Questionnaire Short Form (Gow et al., 2005). Respondents are asked to indicate how accurate they think statements such as "I am interested in people" or "I pay attention to details" are in describing themselves.

G. Descriptive Statistics

Our final sample consists of 900 respondents. Online Appendix II, Table C provides brief sample accounting. We made 458,317 phone calls; 6,459 completed the initial phone screen; 2,617 were eligible for the full study and 3,482 were deemed ineligible. 1,227 agreed to be surveyed and 75.63% of them actually completed the survey. [10]

Appendix Table 2 compares our sample to participants of the 2016 American Communities Survey (ACS), a sample of 3,156,487 individuals from across America. The mean household income for our set of respondents is $47,484, compared with $91,850 nationally. We have a significantly higher fraction of black people – 43.7% in our sample compared to 12.7% in the national average. Conversely, we have a lower fraction of hispanic people – 9.7% in our sample compared to 17.8% in the national average. Our sample is statistically similar to the national average in terms of gender. As one might expect, our sample is less educated than the national average – 48.8% have incomplete college degrees compared to 40.7%, while only 20.8% of respondents have a bachelor's degree or higher in our sample compared to 23.1% nationally. In other words, our sample is more likely to be poor, has a higher fraction of black people and is less educated.

We also compare our sample to a sample of individuals from the National Longitudinal Survey of Youth (NLSY) who experienced poverty in their youth. In contrast to the ACS sample, our sample and the subset of those in the NLSY who experienced poverty in their youth look quite similar.[11] Appendix Table 1 compares 4 demographic variables including individual income as well as some questions that assess locus of control and mental illness that are both contained in our sample and the NLSY. Column (1) contains summary statistics from our sample. Column (2) presents these statistics for the sample of the NLSY who experienced

[10] Appendix Table 3 displays summary statistics on various demographics and poverty level for various samples – (1) phone screener sample, (2) ineligible from phone screener, (3) eligible from phone screener, (4) eligible individuals who agreed to participate and (5) participants who completed the in-person interviews. We also display whether the samples are statistically different from each other in terms of demographics and current poverty status. Compared to participants who did not grow up poor (or, are ineligible for the in-person interviews), participants who grew up poor are more likely to be poor now, are younger, have a higher fraction of black and hispanic people, and are lesser educated. Compared to all participants who were eligible for in-person interviews, participants who finally filled in the paper survey are more likely to be poor now, are younger, more black and less hispanic.

[11] We say an individual "experienced poverty in their youth" in the NLSY sample if a respondent from 2014 was between the ages of 14 and 22 in 1979 and the survey reported that their family was below the poverty line in 1979.

poverty in their youth. Column (3) is identical to column (2) but reweights the observations so that the NLSY data has the same distribution on 3 exogenous variables – age, race, and gender – as our sample.

We begin by comparing our sample to the unadjusted NLSY sample. The average age in our sample is 49, and 53 in the NLSY sample. The difference, 4 years, is statistically significant. As NLSY gathers information on individual and *family* income only, we compare individual income across both samples. The mean individual income in our sample is $28,312 compared to $27,751 in the NLSY sample. The difference, $561, is not statistically significant. Other demographic variables such as gender are also statistically similar. Our sample has more blacks and less Hispanics than the NLSY. We also compare questions from the adult mental illness index that overlap between the two surveys. Our sample has worse adult mental illness on three of the four subcategories and lower self-esteem scores than the NLSY.

Comparing our sample to the adjusted NLSY sample gives similar results except on individual income and fraction of black people. Mean individual income in the adjusted NLSY sample is $24,247 and is statistically smaller than the mean in our sample. Mean age in the adjusted NLSY sample is 53 and statistically larger than the age in our sample, while the percentage of women is 52 and statistically similar. While the adjusted NLSY sample has more Hispanics, it has statisically similar percentage of blacks compared to our sample. With regard to adult mental illness and other psychological traits, the adjusted NLSY sample looks similar to the unadjusted NLSY sample i.e. the sample has better adult mental illness on three of the four subcategories and higher self esteem scores compared to our sample.

H. Correlations with Income

To get a sense of how these new data – unprocessed – correlate with income, Appendix Figures 1(A) - 1(D) displays binned scatter plots of household income on a set of 18 indices individually, which together, encapsulate all 350 questions asked of our respondents. All figures plot a scatter graph, as well as a quadratic fitted line, of the log of household income on binned categories of indices with each observation weighted by its associated survey weight.

The general picture that emerges is that adult income is strongly correlated with mental illness before 16 years of age, psychological traits, family environment, lifetime traumas and neighborhood mobility.[12]

[12] Appendix Figure 1(A) displays the relationship between income and four health-related indices: (a) mental illness before 16, (b) physical illness before 16, (c) psychological index, and (d) diet. Mental and physical illness indices were created as totals of standardized responses to questions on "Childhood Health Experience". Psychological index is the total of 7 sub-indices: resilience, locus of control, growth mindset, grit, self esteem, Big 5 personality traits, and self control. Diet is the total of standardized responses to 2 questions – fraction of days the respondent received three meals and fraction of days he received a balanced diet between the ages of 5 and 12. A detailed description of how each index was created is given in the Online Appendix III.

Both mental illness before 16 and the psychological index show strong correlations with income – income declines as mental illnesses in childhood increase and income rises steeply with more psychological skills. Appendix Figure 1(B) similarly plots six indices which, together, provide a reasonably comprehensive picture of each respondent's childhood family environment. Income is positively correlated with the *quantity* of adult relationships trusted in their childhood, and is also positively correlated with the *quality* of those relationships – individuals who could trust their parents had higher income than those who did not trust

Appendix Table 4 displays pairwise correlation coefficients between any two given indices and provides a good sense of how potential covariates of intergenerational mobility might relate to each other. Of the several coefficients presented, the most noteworthy ones are between adverse childhood experience and mental illnesses before 16 years of age (0.426), adverse childhood experience and traumas experienced before 18 years of age (0.517) and adverse childhood experience and parenting (-0.572). Good parenting is highly correlated with better relationship with parents (0.510) and, consistent with Chetty et al. (2018), neighborhood mobility is highly correlated with fraction of fathers present in zipcode (0.779).

Traditionally, social scientists interested in correlates of intergenerational mobility have estimated models of the following form:

$$income_{t+1} = \alpha + \beta X + \gamma income_t + \epsilon \tag{1}$$

Western and Pattit (2010) use this approach on the National Longitudinal Survey of Youth 1979 data and find that while two-thirds of non-incarcerated low-income men are upwardly mobile, only one in four out of incarcerated men rises out of the bottom quintile of the earnings distribution. Sanbonmatsu et al. (2012) use data from interviews of adults from the "Moving to Opportunity" households and infer that moving into a low-poverty neighborhood during childhood has substantial effects on the physical and mental health of adults.[13] Most recently, Chetty et al. (2018) demonstrate that the only variables that explain racial differences in mobility across geographies (out of 23 analyzed) is the fraction of black fathers present in the census tract and racial bias in the county (measured as scores on Implicit Association Tests and an index based on the frequency of Google searches for racial epithets). The authors estimate that children who grow up in a tract with 10 percentage points more black fathers present have incomes that are 0.5 percentiles higher on average. Conversely, counties with 1 standard deviation higher level of racial bias against blacks have mean income ranks that are 0.8 percentiles lower.[14]

Using this traditional approach on our new data yields some interesting but puzzling results, which are depicted in Figure 1. Five variables are significantly correlated with intergenerational income mobility –

their parents but trusted a teacher or coach instead. Family environment – which encompasses true/false statements such as "we fought a lot in our family", "family members were rarely ordered around", "we didn't say prayers in our family, "we didn't believe in heaven or hell", "family members sometimes hit each other", "everyone had an equal say in family decisions" etc. – is positively related to income and so too, is the quality of a family's social network (defined as the total of standardized responses to questions on if parents' close friends lived in the same neighborhood, graduated from college, worked full time or were a different race). Surprisingly, parenting skills and relationship with parents was not directly correlated with income. These variables are strongly correlated to family environment, however.

Appendix Figure 1(C) displays the same graphs for five childhood experience indices – (a) adverse childhood experience (ACE), (b) risky attitudes as a teenager, (c) trauma before 18 years of age, (d) any trauma in lifetime, and (e) beliefs about success in life. Income levels decline when teenagers exhibit more risky behaviors or when individuals report more lifetime trauma. Surprisingly, however, the relationship between income and adverse childhood experiences is not significant, though ACE and youth mental health have a correlation of almost 0.5.

The final set of graphs are shown in Appendix Figure 1(D) which plot income and three neighborhood indices – (a) neighborhood income mobility, (b) fraction of fathers present in neighborhood, and (c) neighborhood safety index. All neighborhood indices are positively correlated with income levels.

[13] Table 1 gives a review of studies that estimate correlates of intergenerational mobility from various data sources.

[14] Although, black-white wage gaps are smaller in "good" neighborhoods with low poverty, high rates of father presence and low rates of implicit bias, fewer than 5% of blacks live in such neighborhoods.

education, resilience, mental illnesses before age 16, trouble with police before age of 18 and grit. The results are consistent with McKernan and Ratcliffe (2005), Haskins (2008), Baum, Ma and Payea (2013), Aldaz-Caroll and Moran (2001), Sharkey and Torrats-Espinosa (2015) and Western and Pettit (2010).

Surprisingly however, childhood risky behaviors, physical or sexual abuse or neighborhood mobility do not register as significant once one controls for other variables. Of course, they may be operating through variables such as trust of adults and mental health, but if we were designing an intervention based on these data and were not confident about the income production function, one could conclude that increasing education and giving them resilience training – and ignoring parenting, abuse, or risky behaviors – would significantly increase income. Moreover, the results are not robust for different choices of income variables. Using individual income as our outcome, some variables such as district mobility and beliefs about success had an opposite effect of what we expected. This is a known problem is using descriptive methods to assess variable importance with data sets which have many potential explanatory factors (Mullainathan, and Speiss, 2017).

This inspired us to think beyond the traditional approach.

3 Methods

In what follows, we develop a method that one can use to understand which factors from observational data have the greatest potential to increase a pre-specified outcome. In our particular case, we view these variables as potential levers to change in a field experiment designed to increase income mobility and adult well-being. Our method unearths factors that increase mobility directly, as well as the variables that influence those factors, and so on, without assuming the causal structure among the set of data we collected.

We begin with a simple example we can solve analytically.

3.1 An Example

Let there be two types of children reared in poverty: θ_0 and θ_1. Further assume that θ_0 children have low resilience and belong to abusive households. In contrast, θ_1 children have high resilience and belong to non-abusive households.

The probability of graduating from college is different across types: $P\left(Graduate|\theta_0\right) = .05$ and $P\left(Graduate|\theta_1\right) = .95$. We assume

$$income = \alpha * graduation + \epsilon_0$$

Notice, conditional on college graduation, income is independent of type. In other words, a θ_0 that graduates from college can expect the same income as a θ_1.

Traditional methods that don't take into account the graduation production function, will estimate $\widehat{\alpha}$ correctly and will suggest that we should help kids graduate from college. Resilience and childhood abuse don't matter, as long as everyone gets to go to college and has the potential to graduate. Namely, estimating

$$income = \widehat{\alpha} * graduation + \widehat{\beta} * Abuse + \widehat{\gamma} * resilience + \epsilon,$$

yields $\widehat{\alpha} = \alpha > 0$, $\widehat{\beta} = \widehat{\gamma} = 0$.

However, θ_0 children graduating from college is rare, potentially because or and abusive background are affecting graduation rate. In that case, any intervention that lowers the costs for them to enroll (e.g. free test prep or more aggressive guidance counselors) or attempts to make their time on campuses more enjoyable will likely fail because it will not translate into increased graduation. In contrast, if we take into account the graduation production function, we will choose different interventions.

In what follows, we won't try to estimate the equivalent of the graduation production function, but rather, assume that on average it's easier to generate variation that we naturally observe in the data. That is, rather than push θ_0 children to graduate from college, we will try to make the θ_0 children more similar to θ_1 children. Interventions motivated by our approach invest in increasing resilience and counseling abused children.

This approach still may not be effective if θ_0 children are different from θ_1 children on some unobserved characteristics, or observed characteristics that are just impossible to change (e.g. race or genes). In this case, our approach is equivalent to making the θ_0 children who do not graduate from college more similar to the 5% of the θ_0 that do. Assume for instance that those 5% are much more likely to have trusting relationships with adults, compared to the other 95% that do not graduate from college. Then we would like to focus mostly on ensuring there are adults in a child's ecosystem that they can trust, as it seems to be particularly important for college graduation of θ_0 children.

3.2 Using Observational Data to Inform Social Experiments

Imagine that we want to improve some outcome Y (say, log income) and we have data on many observables, X, from a set of individuals. We want to design an experiment that would generate the largest expected increase in income.

Below, we describe a general method to accomplish this based on two assumptions: (1) there is a causal relationship between the set of characteristics in the data, X, and a pre-specified outcome, Y; and (2) the expected costs of an intervention can be approximated by a measure of statistical distance between the pre-intervention and post-intervention distributions of X.

The first assumption ensures there is a problem worth solving – finding correlates that have no potential causal impact is useless. This assumption is not meant to be a reasonable description of reality, but rather something that will be verified in the field experiment. The second assumption is the key innovation of our method. It accounts for the causal links between different X variables in a simple manner. We formalize this intuition below.

Assumption 1. *There is a causal relationship from X to Y such that $Y = f(X) + \varepsilon$ and $f(X) \perp \varepsilon$. If we assumed f was linear, we could estimate this relationship with ordinary least squares regressions, or, if we want to make fewer assumptions, supervised learning algorithms. These approaches, which are standard in the literature, are problematic for the reasons discussed throughout.*

Let there be a process that determines $x \in X$, albeit imperfectly. Suppose there is an intervention $I \in \{0, 1\}$ such that $I = 0$ is status quo and $I = 1$ is an intervention. Let the existing (e.g. status quo) distribution of X be denoted $P(X|I = 0)$, and the post-intervention distribution of X be denoted $P(X|I = 1)$. We assume $I \perp \varepsilon$.

We do not assume that one has any data on interventions so the distribution $P(X|I = 1)$ cannot be directly computed.[15] Moreover, we do not assume that we have a model of all the potential causal relationships of X, which precludes one from writing down a structural model. And, importantly, we don't assume that we can alter $P(X|I = 1)$ in any way we want.

In lieu of making these typical assumptions, let $C(I)$ denote the cost of an intervention I. We assume that, in expectation, this cost is higher the more we change the existing distribution $P(X|I = 0)$. Formally, we will use Kullback-Liebler divergence as a measure of statistical distance between the two distributions (as in Hanson and Sargent, 2001).

Assumption 2. *The expected cost of an intervention is the Kullback-Liebler Divergence*

$$E[C(I)] = D_{KL}(P(X|I = 1) \,||\, P(X|I = 0)),$$

where

$$D_{KL}(P(X|I = 1) \,||\, P(X|I = 0)) = \int_X P(X|I = 1) \log \frac{P(X|I = 1)}{P(X|I = 0)} dX$$

Cost is minimized at $D_{KL} = 0$ (when $P(X|I = 1) = P(X|I = 0)$). For all other choices of $P(X|I = 1)$, $D_{KL} > 0$ and is increasing when the distributions are less similar.[16]

[15] Precisely, what datta would this require.

[16] Formally, in information theory, $D_{KL}(P(X|I = 1) \,||\, P(X|I = 0))$ represents the amount of information gained when learning the data is generated from distribution $P(X|I = 1)$ instead of $P(X|I = 0)$.

Let the expected effect of an intervention, I, on an outcome Y, be denoted $E\left[\Omega\left(I\right)\right]$,

$$E\left[\Omega\left(I\right)\right]=E\left[Y|I=1\right]-E\left[Y|I=0\right]=E\left[f\left(X\right)|I=1\right]-E\left[f\left(x\right)|I=0\right]$$

Now, suppose we want to find an intervention I – a distribution of X – that maximizes the expected effect on income, given some budget constraint: $\max_{P(X|I=1)}E\left[\Omega\left(I\right)\right]$ subject to $E\left[C\left(I\right)\right]<B$.

In Lagrangian form: $L=E\left[\Omega\left(I\right)-\lambda\left(C\left(I\right)-B\right)\right]$, where $\lambda=\frac{\partial E[\Omega(I^*)]}{\partial B}$ is the shadow price of an intervention. We assume decreasing marginal returns – $\frac{\partial^2 E[\Omega(I^*)]}{\partial B^2}<0)$ – which implies that λ is monotonically decreasing in B.

We can simplify the Lagrangian further with two observations. First, $E\left[Y|I=0\right]$ is the status quo, which is constant for all I. Hence, to maximize $\Omega\left(I\right)$ we only need to maximize $E\left[f\left(X\right)|I=1\right]$. Second, B is a constant. Thus, we have the following result:

Proposition 1. *Under Assumptions 1 & 2, the optimal intervention I, solves the following maximization problem*

$$\max_{P(X|I=1)}E\left[f\left(X\right)|I=1\right]-\lambda D_{KL}\left(P\left(X|I=1\right)||P\left(X|I=0\right)\right)\tag{2}$$

for a given value of λ.

When $\lambda\to\infty$ it means we can't change the distribution of X much ($B\to 0$). When $\lambda\to 0$ it means we can change it easily ($B\to\infty$).

The solution to this maximization problem yields the joint-distribution of X after the most cost-effective intervention in expectations. Some of the X variables will be change in order to increase Y directly. Other variables in X will be changed in order to affect Y through other X variables. And some X variables may also change just as a side-effect of the change in the causal variables. While we cannot distinguish between those different cases without additional knowledge, the solution still focuses our search to a much fewer set of interventions.

While conceptually straightforward, this maximization problem can be difficult to solve in practice. We need to estimate two functions: $f(X)$ and $P(X|I=0)$. Estimating $f(X)$ is a standard problem for which one can apply an array of statistical methods ("supervised learning"). To estimate $P(X)$, we need to characterize the distribution of the Xs without any outcome variables; an "unsupervised learning" problem. Finally, we need to solve the maximization problem and find $P\left(X|I=1\right)$ for those estimated values.

In the next sections, we solve the maximization problem under three different sets of assumptions.[17] First, we estimate P assuming X has a multivariate normal distribution and estimate f assuming it is linear. The solution in this case is quite simple. We then use empirical likelihood to estimate both P and

[17] We ignore sample weights in this section for clarity. We prove more general versions of each of the theorems with sample weights in the technical appendix.

f non-parametrically which provides a solution to our maximization problem allowing for flexibility in the relationship between the variables and the relationship between those variables and our outcomes. Finally, we allow for heterogeneity in the distribution of X across individuals.

A. X is Normal, f Linear

Assume X has a multivariate normal distribution and f is linear. With these assumptions, we can prove the following result – which greatly simplifies our problem.

Proposition 2. *Assume $f(X)$ is linear, $X \sim N(\mu_0, \Sigma_0)$ and Assumptions 1&2 hold. Assume also that X is normal after the intervention ($X|I = 1 \sim N(\mu_1, \Sigma_1)$). Then for the optimal choice of I*

$$\mu_1 = \mu_0 + \rho$$

$$\Sigma_1 = \Sigma_0$$

where

$$\nu = \frac{1}{\lambda} COV(X, Y)$$

This proposition simplifies the characterization of the optimal choice for I. First, if X is normal and $f(X)$ is linear, the optimal intervention is an increase of X by a constant vector ρ. Second, this constant is the covariance of X with Y divided by lambda. If we standardize X and Y (to make them unit free) then it's proportional to the correlation coefficient. Thus, raw correlations provide the direction, and if the shadow price is smaller, we proceed further in that direction. And, given our focus on the relative importance of each variable compared to other variables, the value of λ doesn't effect the results.

This is a unique case, where we can analytically solve for the optimal intervention without actually estimating f and P directly.

The intuition described in our example shines through: this method may choose to increase some variables even if they do not effect the outcome directly, once controlling for other variables ($\beta_j = 0$).

Recall, $Y = \alpha Graduation + \varepsilon$ and, now assume a specific linear production function for graduation

$$Graduation = \beta Resilience + \gamma Abuse + \upsilon$$

where $\beta > 0 > \gamma$. Assume that *Resilience*, *Abuse* and υ are normally distributed so the assumptions of Proposition 2 hold.

In this world, resilience and childhood abuse would be correlated with income Y, but not once one controls for graduation. Designing an experiment to intervene only in college graduation, keeping other things fixed, is an intervention in υ.

From Proposition 2, our method will describe the most important correlates of the intervention in the X-space, based on their covariance with Y. The strongest intervention would likely need to be in graduation as $COV\left(Y, Graduation\right) = \alpha V(Graduation)$ which is just α if we normalize all X variables to have standard deviations of 1.

Then, the covariance of resilience can be written as

$$COV\left(Y, resilience\right) = \alpha\beta V(Resilience) + \alpha\gamma COV\left(Resilience, Abuse\right)$$

and similarly childhood abuse. We get that the optimal intervention would affect resilience more when β is higher, so when resilience has a stronger effect on graduation.

It will also be higher when γ and $COV\left(Resilience, Abuse\right)$ are higher in absolute terms: when childhood abuse has a large effect on graduation and they are also (negatively) correlated with resilience. This could be because resilience is decreasing with abuse, which increases graduation even further. Or, because reducing abuse increases resilience as well. Or, because of another factor, that is increasing both simultaneously. In either case, resilience will increase more in the optimal intervention, either directly or throuh ohter channels.

One can also infer how much the optimal intervention would be in the direction of policies that increase graduation directly, while holding other variables fixed, such as free test prep or more aggressive guidance counselors . This is captured in the covariance of Y with the orthogonal part of *Graduation*, which is v. In this example, this can be written as: $COV\left(Y, v\right) = \alpha V\left(v\right)$

Therefore, our method would show that the optimal intervention aims to increase graduation more when $V\left(v\right)$ is higher. This would be the case when there is a lot of variation in *Graduation* which is not driven by resilience or abuse. That is, if there is a significant variation in graduation rate for people with the same level of resilience and childhood abuse, this policy is more likely to be preferred. The intuition is straightforward - if there are many people that are able to graduate from college with low resilience and abused households, then it seems plausible that trying to improve graduation directly is optimal. In contrast, if it's very rare to observe college graduates with low resilience and abused childhoods, it implies that it's very hard to graduate without improving those issues as well. In this case we would want to increase resilience and counsel abused children in order to improve graduation.

3.2.1 Non-Parametric Estimation of $P(X)$ and $f(X)$

The assumptions that X has a normal distribution and f is linear are quite strong. We now outline an approach to estimating both $P(X)$ and $f(X)$ non-parametrically, using empirical likelihood (Owen, 2001).

To estimate P we assume that every x_i we observe in the data has a probability of $\frac{1}{N}$, where N is the sample size. This is the distribution one assumes on the data when using bootstrap methods. The probability to observe an x that is not in the data is set to 0. In symbols:

$$P\left(X=x|I=0\right)=\begin{cases}\frac{1}{N} & \exists x_i\in data \text{ s.t. } x_i=x\\ 0 & \nexists x_i\in data \text{ s.t. } x_i=x\end{cases}$$

Thus, an intervention alters the probabilities of the observed X vectors. The KL divergence for any choice of I is $D_{KL}\left(P\left(X|I=1\right)||P\left(X|I=0\right)\right)=\sum P\left(X=x|I=1\right)\log\frac{P(X=x|I=1)}{P(X=x|I=0)}$.[18]

Our problem simplifies to choosing values for $p_i=P\left(x_i|I=1\right)$ where x_i is the ith observation. The solution is attained from the following proposition:

Proposition 3. *Assume P, f are distributed as above and Assumptions 1 & 2 hold. Then for the optimal choice of I*

$$P\left(X=x_i|I=1\right)\propto w_i^{\lambda^{-1}}$$

Therefore, the solution is a reweighted distribution, that puts larger weights on higher-income individuals. Notice: higher λ means that we can't change much and probabilities remain similar to uniform. Lowering λ puts more weight on high-earners. We use a value of $\lambda=100$, though similar values yield similar results.[19] In the proof appendix we extend this to a more general case, where the optimal intervention cannot change some characteristics (e.g. race, gender), and show the solution is similar.

C. Heterogeneity

What if it's not actually possible to make all people to look more similar to the typical high earning people? Maybe some things in our data are impossible to change. In this case, it's more sensible to try to make people to be more similar to people that have higher income but are more similar to them on other dimensions. In the language of our example, rather than making θ_0 more like θ_1, we can make the θ_0 who don't graduate from college more like the θ_0 who do graduate.

To put this in the context of our framework, we assume that there is heterogeneity in the distribution of X. Hence, it's possible that high earning people are drawing X from a different distribution. This would mean that drawing such Xs could be much more costly for some people. Formally, we will assume that P_i $(X|I=0)$ is different for every observation i. Moreover we will assume that this probability is higher for neighboring values: other values of x we observe in the data for observations that are close. As a result, the cost $C_i(I)$ is lower when we try to change x_i to its neighbors value.

[18] If $P\left(X=x|I=0\right)=0$ (which means that x is not observed in the data), then $P\left(X=x|I=1\right)=0$, otherwise $D_{KL}=\infty$.
[19] We also found that higher values of λ yield results more similar to ones we get under linearity assumptions.

Assumption 3. *Every individual i draws X from the following distribution:*

$$P_i\left(X=x|I=0\right)=\begin{cases}\exp-\frac{dist\left(x,x_{i'}\right)^2}{2\sigma^2} & \exists x_{i'}\in data\ s.t.\ x_{i'}=x\\ 0 & \nexists x_{i'}\in data\ s.t.\ x_{i'}=x\end{cases}$$

and $dist\left(x,x_{i'}\right)$ is Mahalanobis.

The parameter σ will set how much we penalize for distance. When $\sigma\to\infty$ we can turn child i to any other child in the data with equal costs, and so there's no heterogeneity. As $\sigma\to0$, we can only change to the closest neighbor. There is a tradeoff between bias and variance in the choice of σ. High σ will use all data, and would therefore be more biased but with less variance. Low σ will use fewer and closer data, and will therefore be less biased but noisier.We use $\sigma=1$, but different values yield similar results. For the choice of f we will use the same non parametric method we used before and set $\widehat{f}\left(x_i\right)=\log w_i$.

As we've seen before, an intervention I that sets $P_i\left(X_i=x_0|I=1\right)>0$ when x_0 is not in data will make the KL divergence infinite. Therefore we can limit ourselves to intervention that sets some positive probability $P_{ij}=P_i\left(X=x_j|I=1\right)$ where x_j is the jth observation in the data, and P_i is the specific probability distribution of the Xs for child i. Our goal is then to choose values for P_{ij} for every j s.t. $\sum_j P_{ij}=1$.

Proposition 4. *Assume P_i,f are distributed as above and Assumptions 1 & 2 hold. Then for the optimal choice of I*

$$P_{ij}\propto w_j^{\lambda^{-1}}\exp\frac{dist\left(x_i,x_j\right)^2}{2\sigma^2}$$

Intuitively, this exercise is similar to the reweighting in the non-parametric section. The key difference is that now we put more weight on closer neighbors. Therefore, high-income people who look very different from the rest of our data would get a lower weight, compared to the non-parametric case. This captures the intuition that people that look very different, might have their Xs produced in a different way, and therefore an intervention that would try to make all people more similar to them would be less likely to be successful. Overall, under $I=1$ we would have a distribution of X with the same support of our data, that has a higher probability to draw X values of high income people, who are similar to the X distribution in the data.

We choose $\lambda=100$ as we chose in previous sections. We calculate P_{ij} up to a constant, using the above equation, and normalize to get the probabilities sum to one. This gives us a distribution to draw each value of x_j which is $P\left(X=x_j|I=1\right)=\frac{1}{N}\sum P_{ij}$. Using this distribution, we calculate the expectation of each variable, and compare it to the expectation in the data ($I=0$), as we did in previous methods.

3.3 Simulated Data

TO BE INSERTED

4 Results

In this section, we present results gleaned from implementing the methods described above on our new set of data. Each one of the methods yields a new distribution of $P(X|I=1)$, which we compare to the original distribution of the data $P(X|I=0)$. Our primary goal is to detect which variables undergo the biggest changes. We do this by plotting a series of figures with the change for each variable in rank order, for all variables in our dataset that are statistically different from zero.

Fromally, for every variable X_j we first calculate

$$\tau(X_j) = \frac{|E[X_j|I=1] - E[X_j|I=0]|}{\sqrt{V(X_j|I=0)}}$$

where $\tau(X_j)$ is the absolute difference in expectations of a variable under $I=0$ and $I=1$. We divide by $\sqrt{V(X_j|I=0)}$ to make this unit-free.

Second, to make the difference in expectations comparable across methods, we standardize the distribution of $\tau(X_j)$ i.e. we divide $\tau(X_j)$ by its standard deviation across all variables in a given method:

$$\frac{\tau(X_j)}{\sqrt{\sum_{j'}\left(\tau(X_{j'}) - \overline{\tau(X_{j'})}\right)^2}}$$

One can interpret the x-axis in each figure as the units of standard deviation for $\tau(X_j)$. The bars surrounding each coefficient estimate is the 90% confidence interval.

4.1 Income

We begin with log household income as our outcome variable and our preferred specification – non-parametric estimation of P and f. Figure 2(A) The most important correlate of income mobility is education. This is consistent with a large literature on the importance of the quantity of education on income (Card, 1999; Garces et al., 2002; Belfield et al., 2006; Barnett and Masse, 2007; Heckman et al., 2010; Heckman et al., 2013; Elango et al., 2015; Heckman et al., 2016). A close second – and statistically indistinguishable – is resilience. Recall, resilience is the ability to bounce back from stressful situations and is measured by responses to questions such as “It does not take me long to recover from a stressful event”.

Surprisingly, half of the significant correlates of intergenerational income mobility are psychological skills:

resilience, Big 5, self-esteem, self control and grit. Other important variables are whether the respondent was ever in trouble with the police in their youth, had adverse childhood experiences, and the number of adult relationships they trusted.

If we adjust household income by household size, we get similar results though estimates are noisier.[20] If we use individual income as our measure, rather than household income, we obtain a larger set of significant variables. All the variables above are significant along with risky attitudes as a teenager, whether the respondent lived with a mother when they were young, and growth mindset – another psychological skill.

These results are in contrast to much of the literature on the correlates of income mobility, though consistent with Nyhus and Pons (2005), Heckman et al. (2006), Currie and Widom (2010), Mofitt et al. (2011), and Heckman et al. (2013). For instance, we do not find that church going, fraction fathers present in a zipcode, or mobility indices more generally are significant correlates. Generally, there is a larger focus in our results on psychological skills and the ecosystem embodied by children when they are young, which includes interactions with police and other adverse childhood experiences, risky behaviors, and the adults in a child's life.

The Spearman (rank) correlation between the non-parametric method of estimating P and f and assuming that X is multivariate normal and f is linear is .90. But because of the parametric assumptions we have more statistical power which leads to more significant variables. Again, under these assumptions, we get all the variables that we did above plus mental heath before the age of 18, locus of control, family environment, and fraction of fathers present in a zipcode. Similar to above, of the fourteen variables that are significant, seven of them are specific psychological skills.

The correlation between the non-parametric approach and when we account for heterogeneity is .91. All but one variable from the non-parametric approach continues to be significant after we allow for heterogeneity and they are the highest ranking correlates (the exception is number of adults trusted). Because of smaller standard errors, when we allow for heterogeneity we have the following additional correlates: family environment, parenting, family network, risky attitudes as a teenager and three additional psychological skills (locus of control, growth mindset, and self control).

Different methods offer modest differences in the specific variables that are gleaned to be significant. But the general pattern is robust. Education, psychological skills, trouble with the police, and adverse childhood experiences are *always* significant, independent of method. This is consistent with recent evidence that education centric interventions designed to increase income among the poor – so-called No Excuses charter schools – may have little impact on mobility (Dobbie and Fryer, 2016). And, suggests that these interventions would be more successful if one simultaneously worked to increase psychological skills and the number of adults trusted, and reduce trouble with the police and other adverse childhood experiences.

[20] We adjust income for household size using the same method employed to calculate the Census Supplement of Poverty Measure (U.S. Census Bureau, 2017). A detailed description of the adjustment is provided in the Data Appendix.

Analysis of Subsamples

Appendix Figures 2(A) - 3(C) explore the sensitivity of our income correlates across a variety of subsamples of the data. We report our estimates that assume X is normal and F is linear separately by race, gender and parental income. We opt for this specification given its high correlation with the non-parametric approach and smaller standard errors.

For each division we plot the variables that are significant for both groups, and the variables that are significantly different between groups (both at the 90% level). For race, we find that two variables are significantly different between blacks and whites. Consistent with Chetty et al. (2018) we find that high mobility zipcodes are significantly more helpful to whites. We also find that number of adults one could trust and whether one could trust any adults in their childhood is operating in opposite directions for blacks and whites; while it is increasing black's income, it is decreasing in white's income. Although we are not certain about the mechanism that drives this difference, we see that for all respondents that said "yes" to trusting adults in their childhood, whites had a significantly higher fraction of unemployed fathers than blacks. So white respondents may have depended on fathers that were untrustworthy which could have resulted in lower adult incomes.

With subsamples based on gender, we find that family network seems to be much more important for girls. Other variables have statistically similar impacts on boys and girls.

Finally, we split our sample by parents income. We find that two variables related to parents are going in opposite directions. For people who grew up in deeper levels of poverty, income is higher for worse parents behavior.

4.2 Adult Well-Being

Thus far, we have concentrated on variants of household and individual income as outcomes. Even for economists, however, there is more to life than income. In this section, we explore a wider definition of adult well-being by including adult physical health, mental illness, and alcohol and drug abuse.

Mental Illness

The correlates of mental illness are quite different from those correlated with income. Unsurprisingly, six of the top eight correlates of adult mental health are psychological skills measured in adulthood. It is unclear what this means. Ideally, the psychological skills would be similar in childhood and thus interventions on those variables may prevent adult mental illness. It is also plausible however, that whatever is associated with adult mental illness is also associated with lower values of general psychological skills.

More interesting, risky attitudes as a teenager and mental health as a teenager are also associated with adult mental health. Education, physical illness in childhood and adverse childhood experience are also associated with adult mental health in the expected directions. Fathers present in zipcode, whether the respondent lived with their father as a child, trouble with police, family environment, and neighborhood safety are also all significant correlates of adult mental health. The similarity between these results and those from the Moving to Opportunity experiment are striking. In that experiment, moving poor individuals to less poor neighborhoods was associated with significant improvements in mental health.

Alcohol and Drug Abuse

The correlates of alcohol and drug abuse are interesting and intuitive. The most important correlates are risky attitudes as a teenager and self control, followed by trouble with police, mental health before sixteen years of age, and grit. Other variables include various parenting variables and family environment and neighborhood safety. It is important to note, education is not in the top 10 of most important variables. The variables above are more important if one wants to reduce drug and alcohol use.

Physical Health

The top correlates of adult physical health are surprisingly intuitive. The variable physical illness before 16 is now among the top variables, as there is some correlation between physical illness in childhood and adulthood. Good diet is also associated with better adult health. Just as with adult mental illness, adult physical health are also highly correlated with psychological skills, and childhood mental illnesses. Other top correlates are education and risky attitudes as a teenager.

Analysis of Subsamples

Observing the differences of correlates by race we see that, similar to household income, trusting adults during childhood leads to better mental health for black kids but worse mental health for white kids. Living with mother or stepmother during childhood leads to worse mental health outcomes for black kids. This may be an indicator of worse outcomes for black kids who have grown up with absent fathers, a result consistent with Chetty et al. (2018). The only other variable that is statistically different for blacks and whites and which affects an outcome in opposite directions is family network. For black children, strong family networks lead to worse adult physical health while for white kids, a strong family network leads to better adult physical health. Without more knowledge of how one's network looks like, it is difficult to surmise the reason behind this result.

Splitting subsamples by gender, we observe that all correlates impact adult mental health in the same direction for both boys and girls. If anything, girls' mental health seems to be impacted to a higher extent than boys' mental health for any given correlate. With regard to adult drug and alcohol use, the only suprising result that we have which is difficult to explain is that girls with higher beliefs about future success seem to have higher drug and alcohol use. The correlate is negative and insignificant for boys. For adult physical health, we see that living with a grandparent might have a negative impact on future physical health for boys. The same result does not apply to girls.

Our final subsamples are obtained by splitting across parental income. In general, just as with household income, we see that children with lower income parents require stronger intervention for adult mental health and adult drug and alcohol use.

5 Discussion

Our analysis of intergenerational mobility has developed a new set of facts. Using newly collected data and a new method, we argue that to increase income among the poor we need a multipronged strategy that focuses heavily on the ecosystem children inhabit, their psychological skills to navigate the situations they endure, and, importantly, education. These results are suggestive. We caution against a rush to policy, but rather a rush to experimentation with the goal of boosting income among those who are born poor.

Our analysis has several important caveats.

First, our locations are not representative. Yet, as we argued in section 2, our sample of respondents who grew up poor in Memphis, Tulsa and New Orleans look similar to a nationally representative sample gathered from the 2014 wave of NLSY who were between the ages of 14 and 22 and below the poverty line in 1979.

Second, our datapoints are retroactive. We ask respondents to recall their home environment, parenting details, and experiences from childhood, many years removed. Not only is memory unreliable, but there may be systematic biases in the types of narratives individuals believe about their life trajectory. That is, individuals who are more upwardly mobile may emphasize the highlights of their childhood experience whereas individuals who are less successful may emphasize the lowlights. Assumption 1 dealt with this issue theoretically. But, the empirical importance of these potential biases is untestable with current data.

In addition, our variables designed to assess psychological capital – grit, growth mindset, resilience, locus of control, Big 5 personality traits, self esteem and self control – are contemporaneous. It is possible that respondents who have escaped poverty feel more resilient or have higher self esteem. This is partially testable.

To understand how this might affect our results, we analyze a longitudinal dataset where respondents are queried about their psychological traits in multiple waves. The NLSY assesses respondents' locus of control in 1979 and then again in 2014. We estimate the correlation between income in 2014 and locus of control in 2014 – which is similar to what we do in our analysis – and then separately, estimate the correlation between income in 2014 and locus of control in 1979. If the correlation coefficient from both specifications are statistically similar, it provides some evidence that an internal locus of control has a positive impact on adult income regardless of when this locus of control was measured.

Appendix Figure 4 presents the results. Similar to our data, locus of control is positively correlated with income. The slope using our dataset is 0.07 (0.03) and 0.12 (0.02) in the NLSY data when regressing current income on current measures of locus of control, both have p-values below conventional levels. Importantly, when we plot current income on locus of control in youth using the NLSY data, the slope is 0.05 (0.02) and is also significant. The p-value of the difference in coefficients on locus of control from the 3 plots is 0.158. This shows that the correlation between income and locus of control from our dataset is statistically similar to the correlation between income and locus of control from the NLSY sample regardless of when locus of control is measured in the NLSY sample.

Third, our results are best seen as a list of "sufficient" – not necessary – variables to increase a particular outcome. They are correlates, not causal estimates, though some of the variables have been shown in other work to have a causal relationship. Table 2 summarizes the literatures that estimate the causal relationship between variables we believe our significantly correlated with income, separately. We do not have estimates of the total derivative, but there are several important partial derivatives. It is a reasonable exercise to believe that as long as X_1 is positively causally related to Y and X_2 is positively causally correlated with Y, then as long as X_1 and X_2 are positively correlated with each other, we would expect an intervention in both X_1 and X_2 to increase Y. Appendix Table 4 already shows that the most important correlates with household income are positively correlated with each other, so positive partial derivatives from literature would be a good guess about positive total derivatives from potential interventions.

Years of education has a causal impact on income. Card (1999) gives an incredible survey of literature on causal relationships between education and earnings. He estimates that an additional year of schooling can increase wages by 2-11%. Heckman et al. (2016) study the subsample of males extracted from NLSY 1979 to estimate the positive increase in earnings caused by an additional year in high school or college. Besides education in higher grades, there is also a vast amount of literature on the efficacy of early childhood education on earnings. Belfield et al. (2006), Heckman et al. (2010), Heckman et al. (2013) measure the positive impact of the HighScope Perry Preschool Program on participants' earnings. In the same vein, Barnett and Masse (2007), Elango et al. (2015) calculate the net effect of the Abecedarian program on adult earnings and Garces et al. (2002) and Elango et al. (2015) calculate the same estimate for Head Start participants. Table 2 gives details about these papers and the corresponding causal estimate calculated by each.

There also exists a diverse set of papers studying the impact of higher scores on the Big 5 Personality Traits on earnings. Nyhus and Pons (2005) study 888 workers aged 16-65 who were part of the CentER Saving Survey in Netherlands and conclude that higher scores on different personality traits like agreeableness and emotional stability leads to higher wages for men and women. Heckman et al. (2013) study 123 HighScope

Perry Preschool Program participants and infer that their increase in adult incomes is causally due to improvements in Big 5 personality traits.

Heckman et al. (2006) also estimate the effect of higher self esteem and more internal locus of control through their study of NLSY 1979 participants and conclude that a 1 standard deviation increase in non-cognitive ability increases hourly wages by 11.2%. Moffitt et al. (2011) study sibling pairs from the Dunedin Multidisciplinary Health and Development Study in New Zealand and state that higher self control leads to higher adult incomes.

Currie and Widom (2010) track 807 individuals from a Midwestern metropolitan county which include children who have court substantiated cases of childhood physical and sexual abuse and neglect and study their labor market performance compared to a matched sample of non-abused and non-neglected children. They estimate that child maltreatment reduces adult earnings by approximately $5000.

Finally, there is also literature on the causal impact of youth criminal behavior on adult income. Allgood et al. (2007) analyze 439 sibling pairs from NLSY 1979 and estimate that a criminal charge when young leads to a reduction of adult income by 22% while a criminal conviction reduces adult income by 36%.

This type of analysis is, at most, speculative. Whether the bundle of variables we view as significant correlates can increase income is an experimental question. Will it work? We can't know in the abstract. But, with the benefit of hindsight, we can use our method on the detailed within-school data collected in Dobbie and Fryer (2013) and then compare the suggested optimal intervention from our to the intervention implemented in Fryer (2015).

Dobbie and Fryer (2013) study data collected from 39 charter schools and correlate it with estimates of school effectiveness. They find that traditionally collected input measures – class size, per pupil expenditure, fraction of teachers with no certification, and the fraction of teachers with advanced degree – are not correlated with school effectiveness. In contrast, policies suggested by qualitative research – frequent teacher feedback, the use of data to guide instruction, high-dosage tutoring, increased instructional time, and high expectations – explains 45% of the variation in school effectiveness.

Using the same data, we implement our method. The results are interesting and are shown in Appendix Figure 5. The significant correlates of high quality schools are teacher feedback, instructional time, high expectations and high quality tutoring. Interestingly, non-certified teachers are strongly negatively correlated with school effectiveness while data driven instruction is not significantly correlated with school effectiveness.

Fryer (2015) implemented 4 of these and demonstrated large impacts in math and less in reading, a pattern closely resembled in the achievement-increasing charter schools they were gleaned from. Whether Fryer (2014) would have had significantly different results if they had removed non-certified teachers as the suggested correlates from our method shows, is unknown. However, it is important to note that given that literature suggests that certified teachers, better teacher feedback, higher instructional time, high expectations and high quality tutoring have positive partial derivatives with respect to achievement and the data suggests that they are positively correlated with each other, we may reasonably expect an intervention using the suggested correlates from our method to have a positive effect on math and reading scores.

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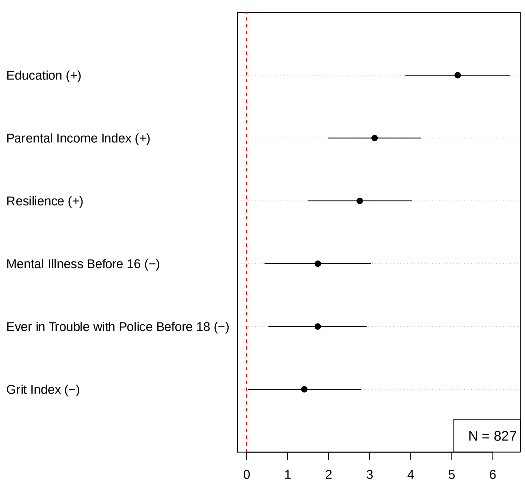
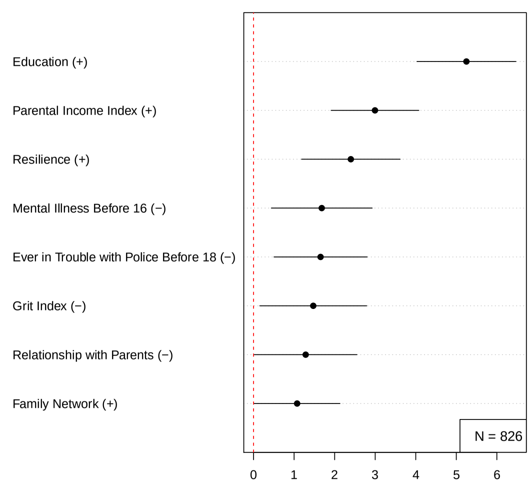
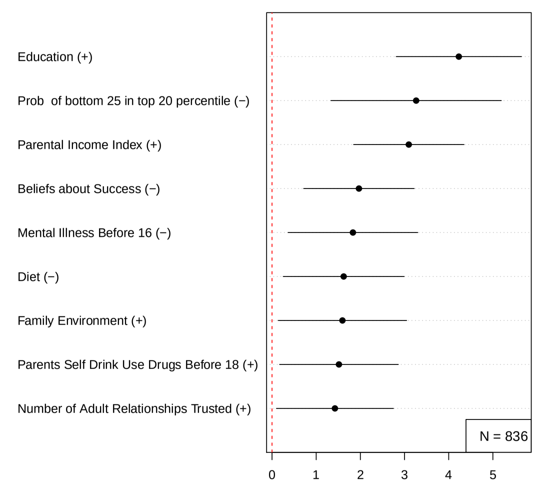
Figure 1: OLS Method



A: Household Income

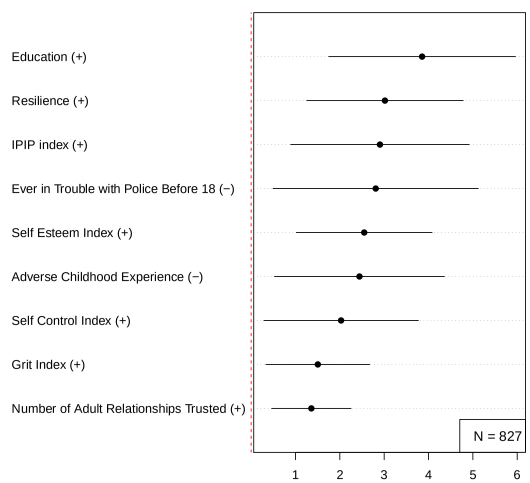


B: Adjusted Income

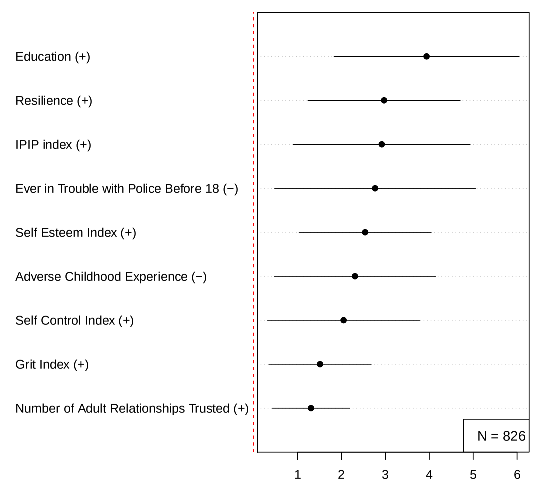


C: Individual Income

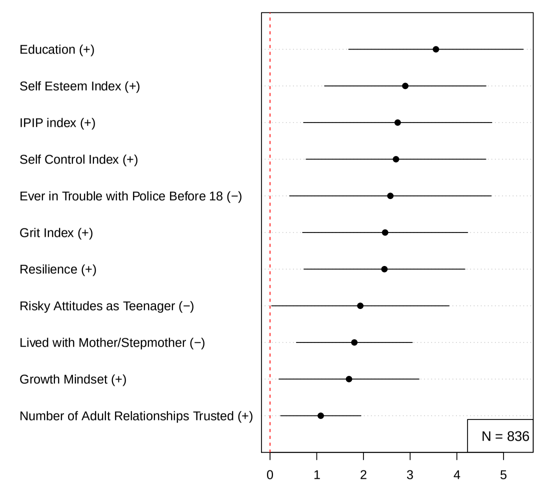
Figure 2: Non-Parametric Method



A: Household Income

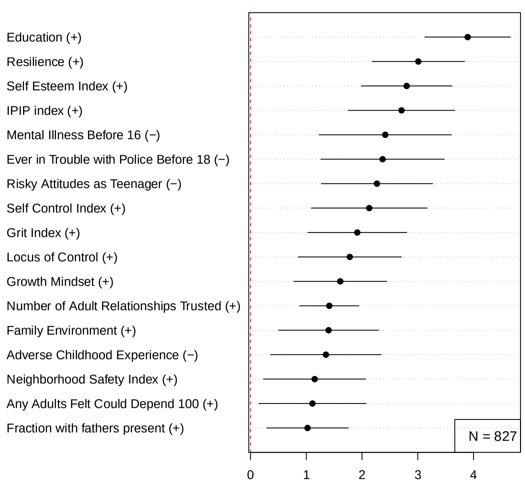


B: Adjusted Income

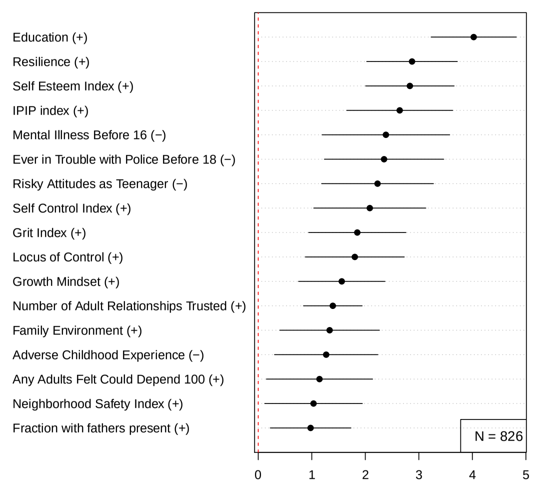


C: Individual Income

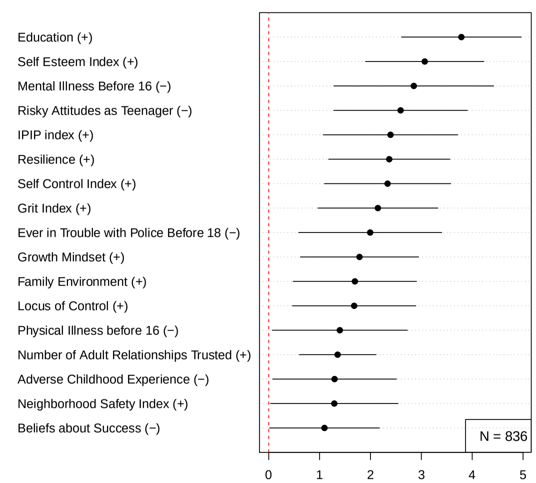
Figure 3: Partial Correlations



A: Household Income

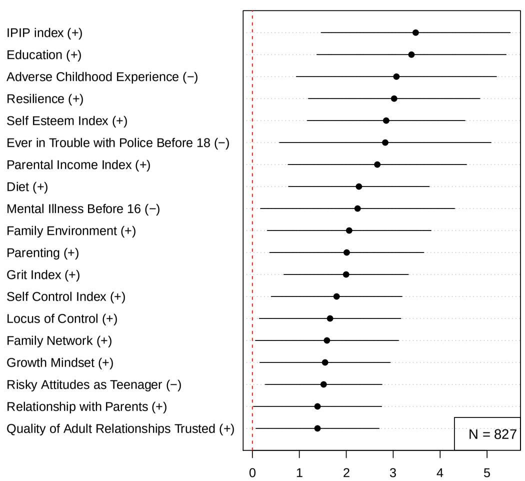


B: Adjusted Income

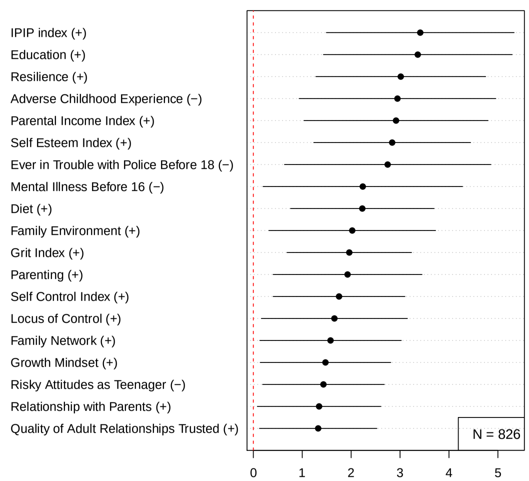


C: Individual Income

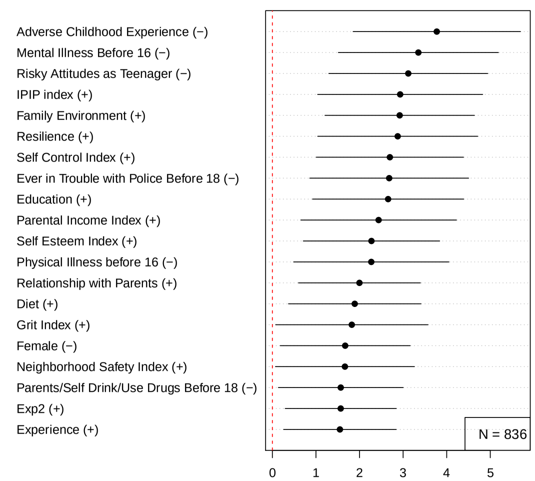
Figure 4: Nearest Neighbor



A: Household Income

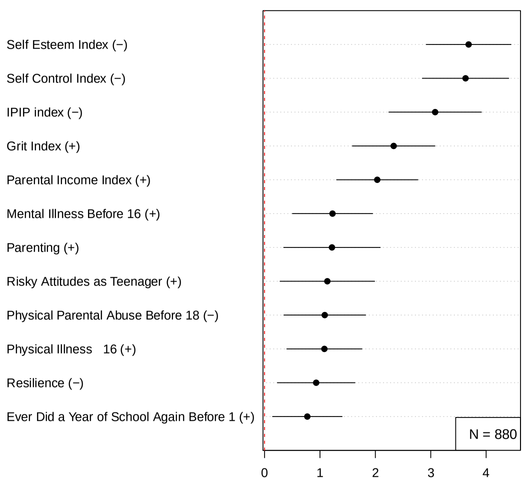


B: Adjusted Income

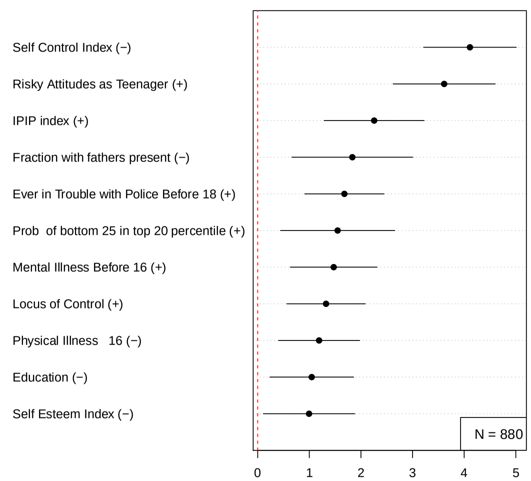


C: Individual Income

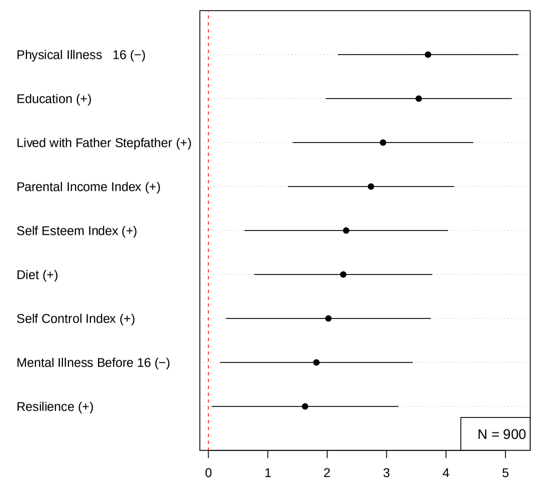
Figure 5: OLS Method, Alternative Outcomes



A: Adult Mental Illness

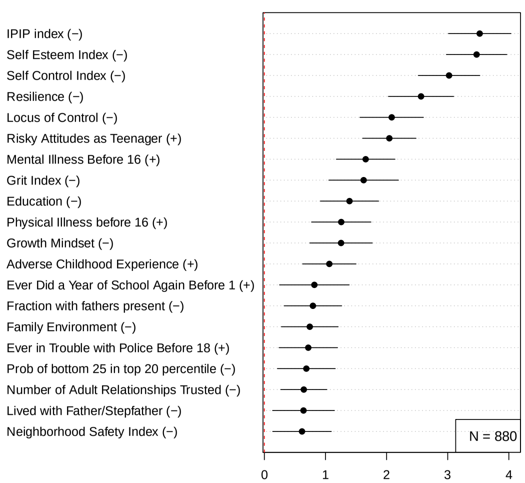


B: Drug and Alcohol Use

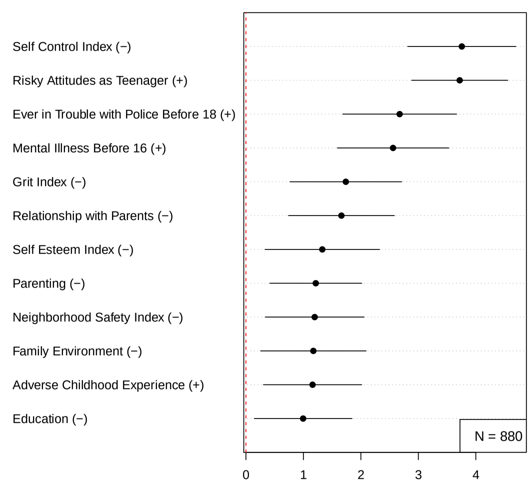


C: Adult Physical Health

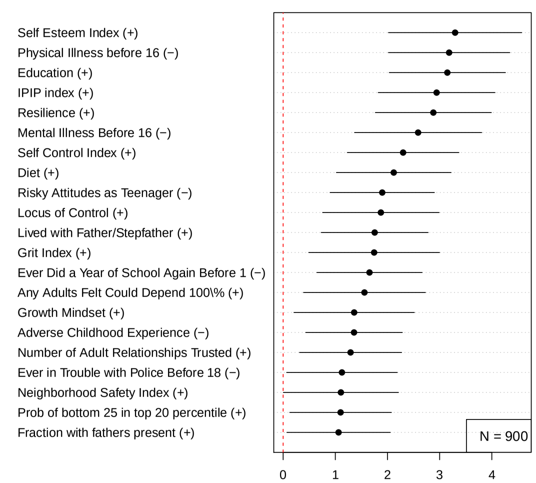
Figure 6: Non-Paramteric Method, Alternative Outcomes



A: Adult Mental Illness

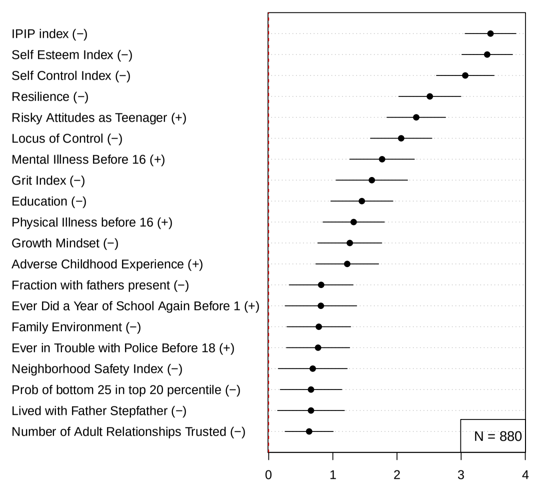


B: Drug and Alcohol Use

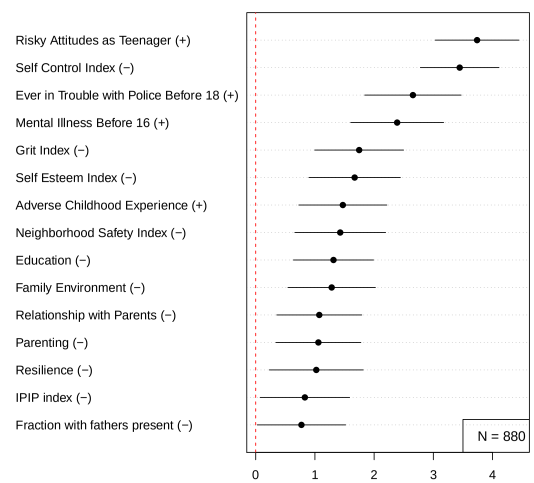


C: Adult Physical Health

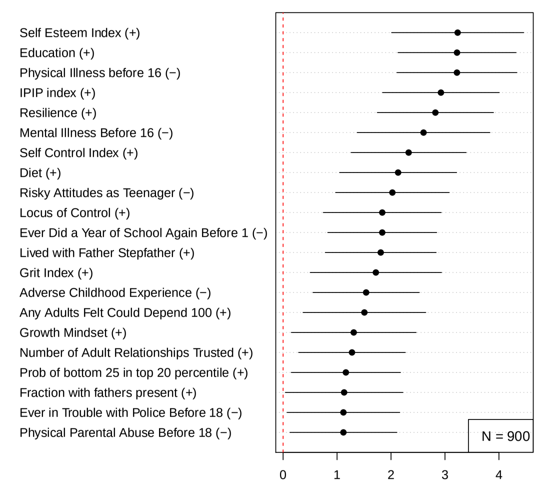
Figure 7: Partial Correlations, Alternative Outcomes



A: Adult Mental Illness

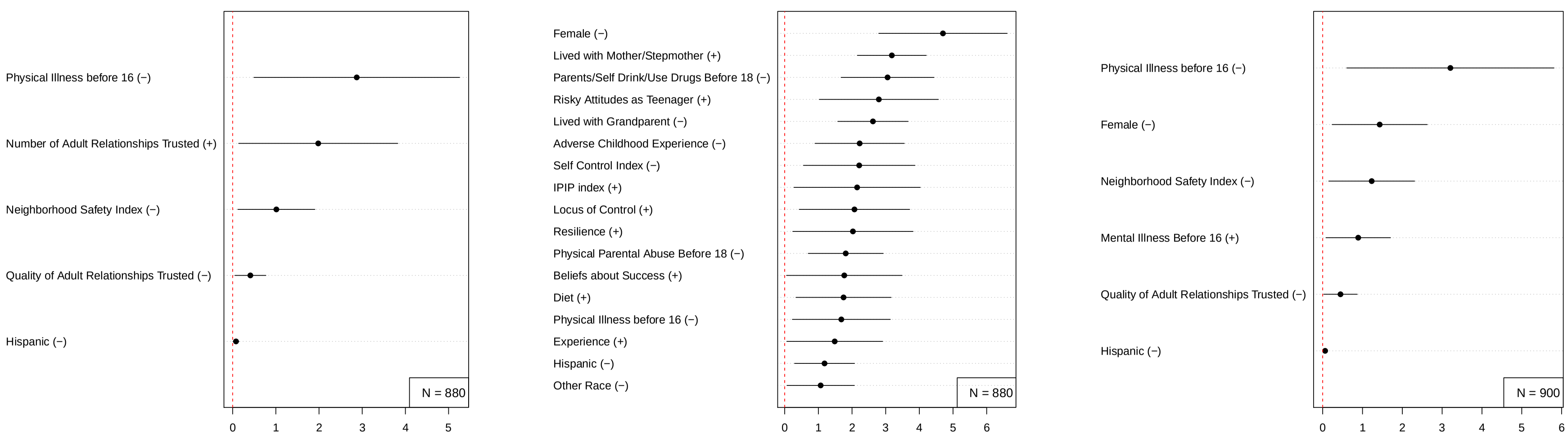


B: Drug and Alcohol Use



C: Adult Physical Health

Figure 8: Nearest Neighbor, Alternative Outcomes



A: Adult Mental Illness

B: Drug and Alcohol Use

C: Adult Physical Health